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# A Survey Paper on Brain Tumor Detection

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***Abstract:*** This The goal of this study is to identify brain tumours and improve care for those who are suffering. Tumours are the name given to the aberrant cell growths in the brain, and the word "cancer" is used to describe malignant tumours. For the identification of cancerous brain tissue, CT scans, MRI scans, or Positron Emission Tomography (PET) scans are frequently employed.For the detection of brain tumours, further methods include molecular testing, lumbar puncture, and cerebral angiogram. MRI and PET scan pictures are used in this investigation to examine the illness state. The goals of this study are to (i) recognise aberrant images, (ii) segment tumour regions, and (iii) determine the stage of the malignancy. The segmented mask can be used to predict the tumour density, which will aid in treatment. A deep learning algorithm is used to analyse MRI pictures and find anomalies. The tumour region is divided using multilevel thresholding. The number of cancerous pixels can be used to determine the density of the affected area.

***Index Terms* - Medical Image Processing, Artificial Neural Network, Brain Tumor, MRI, PET scan.**

## I. INTRODUCTION

Early diagnosis and treatment of brain tumors contribute to earlier diagnosis, which lowers the mortality rate. Image processing has become increasingly common in recent years and is also an essential component of the medical industry. Brain tumors are brought on by the abnormal cell development in the brain. The term "intracranial neoplasm" is also used to describe brain tumors. Malignant and benign tumors are the two types of tumors. Based on visual characteristics and an investigation of the soft tissue's contrast texture, distinct forms of brain tumors are typically distinguished using MRI or PET scan sequences. The World Health Organization (WHO) has classified more than 120 kinds of brain tumors into four tiers based on their level of aggressiveness. The major objective of our study is to create a deep learning-based technique for quickly and precisely identifying brain tumors. This notion, put out to assist medical experts in spotting tumors in the earliest stages, will not only help improve patient outcomes but also support the creation of more specialized treatment regimens.
Our model's contributions are as follows:

- It uses deep learning techniques to detect brain tumors with precision;
- It can be trained on big datasets to increase accuracy and efficiency;
- It is inexpensive;
- It is simple to integrate into existing medical workflows.

## II. LITERATURE REVIEW

[7] Logeswari, T. and Karnan, M., 2010. An improved implementation of brain tumor detection using segmentation based on hierarchical self-organizing map. International Journal of Computer Theory and Engineering,
In the early 2009, segmentation was an important process for extracting information from complex medical images, with wide applications in the medical field. The main objective of image segmentation was to partition an image into mutually exclusive and exhausted regions such that each region of interest was spatially contiguous, and the pixels within the region were homogeneous with respect to a predefined criterion. Homogeneity criteria widely used included values of intensity, texture, color, range, surface normal, and surface curvatures. During the past decade, many researchers in the field of medical imaging and soft computing made significant progress in the field of image segmentation. Image segmentation techniques were classified based on edge detection, region or surface growing, threshold level, classifier such as Hierarchical Self-Organizing Map (HSOM), and feature vector clustering or vector quantization. Vector quantization proved to be a very effective model for the image segmentation process. But there where issues with approach so it needed to be farther improved.

[8] Farias, G., Santos, M., Lopez, V.: Brain tumor diagnosis with Wavelets and Support Vector Machines. In: International Conference on Intelligent System and Knowledge Engineering, Xiamen, November 17-19, pp. 1453–1459 (2008) 10.1109/iske.2008.4731161
An intelligent strategy and a synergy of signal processing techniques were used to identify several forms of human brain tumors in order to support the histological diagnosis, according to G. Farias et al.'s 2008 proposal [8]. The wavelet-SVM (support vector machine) classifier combined the wavelet transform with SVM to categorise the biological spectra after shrinking their size and extracting their key features. Each of the techniques' configuration factors and their effects on clustering were examined. The classification results were encouraging, especially in light of the exclusion of medical expertise.

[9] M. U. Akram and A. Usman, "Computer aided system for brain tumor detection and segmentation," International Conference on Computer Networks and Information Technology, Abbottabad, Pakistan, 2011, pp. 299-302, doi: 10.1109/ICCNIT.2011.6020885

In 2011 another proposed technique was tested for brain tumor segmentation accuracy using 100 MR images of different patients. The images used for testing were of size 676x624 pixels, eight bits per color channel, and contained brain tumors of different sizes, shapes, and intensities. To check the accuracy of the automated segmented tumor area, the tumor from all images was manually segmented by an ophthalmologist, and the manually segmented images were used as ground truth. The true positive rate and false positive rate were calculated to evaluate the accuracy of the proposed method. The experimental results for different MR images containing tumors of different shapes and sizes showed that the proposed method accurately extracted brain tumors. The results of tumor segmentation for MR images were summarized in table-I, showing the average accuracy and standard deviation compared with the ground truth. Average accuracy was computed by counting the total number of pixels correctly classified.

[10] Mustaqeem, Anam, Ali Javed, and Tehseen Fatima. "An efficient brain tumor detection algorithm using watershed & thresholding-based segmentation." International Journal of Image, Graphics and Signal Processing 4.10 (2012): 34.

New segmentation techniques were widely employed in 2012 in the field of medical image analysis, particularly in the detection and diagnosis of brain tumors. Before using alternative segmentation techniques, threshold segmentation was frequently utilised as a pre-processing step. In order to avoid over- or under-segmentation, watershed segmentation requires precise marker selection. It was beneficial for separating overlapping or touching items in a picture. Binary images were processed with morphological operators including erosion and dilation to reduce noise and distinguish regions of interest. Overall, these segmentation techniques were crucial tools for studying medical images, increasing the precision of diagnosis, and designing effective treatments.

[11] Amin, J., Sharif, M., Raza, M. et al. Brain tumor detection: a long short-term memory (LSTM)-based learning model. Neural Comput & Applic 32, 15965–15973 (2020).

In 2013 Multi-sequence MRI images were improved in quality using N4ITK and Gaussian filters before being processed through a deep long short-term memory (LSTM) model in a novel method for automated brain tumor classification. The LSTM model had four layers, with the best hidden units (HU) being chosen for each layer after rigorous testing. On multiple datasets, such as BRATS 2012–15, 2018, and SISS–ISLES 2015, the results were validated, and high dice similarity coefficient (DSC) scores ranging from 0.95 to 1.00 were obtained. Real patient cases were also tested, and a DSC score of 0.97 was obtained, proving that the suggested method can help radiologists classify brain tumors effectively.

[12] Tanzila Saba, Ahmed Sameh Mohamed, Mohammad El-Affendi, Javeria Amin, Muhammad Sharif, Brain tumor detection using fusion of hand crafted and deep learning features,Cognitive Systems Research,Volume 59, 2020,

In 2015 proposed research focuses on the precise segmentation and early detection of brain tumors utilising imaging methods from medicine. Actual lesion symptoms are precisely segmented using the Grab cut approach, and features are extracted using a transfer learning model tailored to VGG-19, which are then blended with manually created features (shape and texture) using a serial-based method. Entropy is employed to optimise these features for quick and accurate classification, and the classifiers are given the fused vector. With high dice similarity coefficients (DSC) of 0.99 on BRATS 2015, 1.00 on BRATS 2015, the model is tested on the most prestigious medical image computing and computer-assisted intervention (MICCAI) challenge databases. Using this concept, early detection may help patients avoid the negative impacts of brain tumors.

[13] Arti Tiwari, Shilpa Srivastava, Millie Pant,Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019,Pattern Recognition Letters,Volume 131,2020,ISSN 0167-8655,

In 2019, For the purpose of identifying anomalies in brain tissues, including brain tumors, magnetic resonance imaging (MRI) and computer tomography (CT) scans are two frequently employed medical imaging procedures. However, because it is non-invasive and has more benefits than CT scans, MRI is preferable. Because tumor shapes, sizes, and locations can vary, segmenting brain tumors from MRI images can be difficult. To increase the precision and effectiveness of brain tumor segmentation and classification, researchers have investigated a variety of methods, including deep learning and metaheuristic methods. Artificial neural networks are used in deep learning techniques to extract features and discover patterns from massive datasets. These methods have produced encouraging outcomes in the precise segmentation of brain tumors from MRI images. On the other hand, metaheuristic approaches are optimisation algorithms that draw their inspiration from organic processes like evolution and swarm intelligence. It has also been investigated to enhance the precision and effectiveness of brain tumor segmentation and classification through the hybridization of deep learning and metaheuristic methods. It is possible to get better results by combining the advantages of the two approaches. For instance, features can be extracted using deep learning, and segmentation can be optimised using metaheuristic methods. These methods seek to increase the segmentation process' accuracy and effectiveness in order to aid in the early identification and management of brain tumors.

[14] Javeria Amin, Muhammad Sharif, Mussarat Yasmin, Steven Lawrence Fernandes,A distinctive approach in brain tumor detection and classification using MRI,Pattern Recognition Letters,Volume 139,2020,ISSN 0167-8655,

Using several methods for lesion segmentation, the proposed automated system seeks to distinguish between malignant and non-cancerous brain MRI. For each lesion candidate, the approach chooses a set of characteristics, such as shape, texture, and intensity. Then, a Support Vector Machine (SVM) classifier is used to compare the proposed framework's accuracy using various cross-validations. On three benchmark datasets, the approach is validated, and the average accuracy, area under the curve, sensitivity, and specificity are all 97.1%, 91.9%, 0.98. This proposed paradigm can diagnose tumors more precisely and quickly than existing approaches. The accuracy of tumor detection in brain MRI is increased with the use of SVM classifier and a variety of feature sets. The suggested technique can be utilised as an automated tool to help medical personnel swiftly and accurately identify brain tumors, improving diagnosis and treatment.

[15] Marzieh Ghahramani, Nabiollah Shiri, Brain tumor detection in magnetic resonance imaging using Levenberg–Marquardt backpropagation neural network, IET Image Processing, 10.1049/ipr2.12619, 17, 1, (88-103), (2022).
The segmentation and classification of brain tumors using a 3D convolutional neural network (CNN) is the suggested approach in this study. The 2015, 2017, and 2018 datasets from the BraTS challenge were used as three separate datasets for validation. The feedforward neural network (FNN) was utilised as the primary classifier in this study, with discriminant analysis (LDA), k-nearest neighbour (KNN), decision trees (DT), and support vector machines (SVM) also being used for comparison. Several characteristics, including accuracy, error rate, and time, were examined to assess the performance of the suggested strategy. Additionally computed to assess segmentation performance was mini-batch accuracy. The findings demonstrated that, in terms of accuracy and error rate, the suggested technique performed better than the other classifiers.

[16] Shamsudheen, Shermin, Geman, Oana, Izdrui, Diana Brain Tumor Detection and Classification by MRI Using Biologically Inspired Orthogonal Wavelet Transform and Deep Learning Techniques, SN 2040-2295,2022
To enhance performance and streamline the segmentation process, the proposed system makes use of deep learning classifiers and Berkeley's wavelet transformation. The method entails employing the GLCM method to extract important characteristics from each segmented tissue, followed by a genetic algorithm for feature optimisation. The proposed system should be able to precisely define the tumor area's bounds from the preprocessed image, segment the region using Berkeley's wavelet transformation, and identify the tumor region with high precision and accuracy using classifiers like Nave Bayes, SVM-based BoVW, and CNN algorithm. The final result is assessed using the following metrics: precision, sensitivity, specificity, Jaccard's coefficient, spatial overlap, AVME, and FoM. The suggested method works well for identifying tumors in MRI images. The suggested approach has a number of benefits over the ones already in use. The accuracy of tumor detection and segmentation is greatly increased by the application of deep learning classifiers. The feature extraction procedure is further improved by the genetic algorithm optimisation, which also minimises false positive outcomes. Even in the presence of other abnormalities, the method can pinpoint the tumor location precisely and handle multislice MRI sequences. Additionally, because the suggested technology can process MRI pictures and automatically detect and classify tumors, it may lessen the workload of radiologists. A more thorough examination of the properties of tumor tissue is possible with the aid of BWT and GLCM features, which can help with treatment planning and monitoring.

## III. APPROACH WORKS

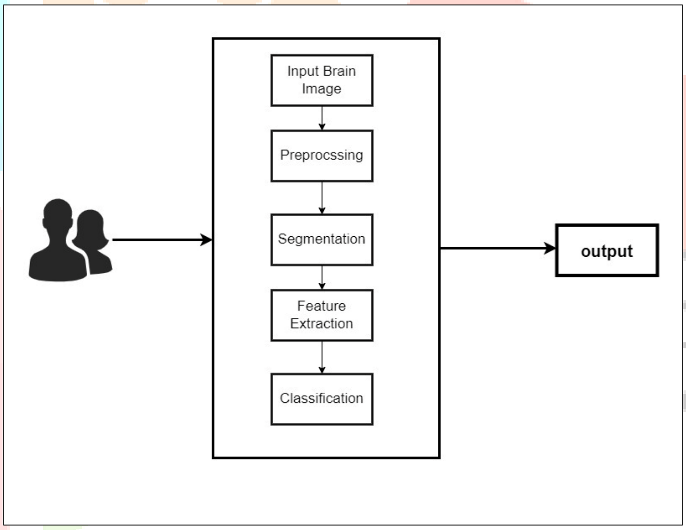


Fig: system architecture

1. Image Collection:

   Magnetic Resonance Images (MRI) are used as the system's input data. The system can function more easily because to the collection and usage of these MRI pictures.

2. Image Preprocessing:

   The image is subjected to a number of pre-processing techniques, including image registration, bias field correction, removal of extraneous tissues from the brain, noise removal, skull-stripping, and image enhancement. It is also possible to use other methods like intensity normalization and image resampling [4].

3. Image Segmentation

   In order to segment an image, it is required to extract the distinctive identifiers of the image, such as texture, shape, and color. Depending on the imaging modality used, different feature extraction techniques are applied. For instance, while intensity-based characteristics are better suited for CT imaging, texture analysis is frequently employed for MRI [4] [5] [6].

4. Feature Selection:

   Segmentation is used to extract changes in the brain, visualize and evaluate the anatomical structure of the brain, and, if necessary, plan for surgery. The tumor size and location, the imaging modalities being employed, and the level of automation required all play a role in the segmentation method selection. Methods that are manual, completely automatic, and semi-automatic are frequently employed [4] [5] [6].

5. Post-processing or Classification:

   Post-processing is altering the image to get a better outcome, such as local constraints, shape constraints, and regularisation of the spatial data. The tumour is discovered in this phase because it offers a clear view of the tumor and its location. Additionally, volume, shape, and texture features can be extracted through statistical analysis of the segmented sections and used for tumor classification and grading as well as treatment planning.

## IV. NEURAL NETWORK ARCHITECTURE

1. Input Layer:
   The input layer of the neural network is a 2D convolutional layer (Conv2D) with 32 filters of size 3x3, using the 'relu' activation function. The input shape to this layer is (IMG_SIZE, IMG_SIZE, 3), where IMG_SIZE is the size of the input images (64 in this case).

2. Max Pooling Layer:
   A max pooling layer (MaxPooling2D) with a pool size of 3x3 is added after the first Conv2D layer to reduce the spatial dimensions of the output feature maps.

3. 2nd Convolutional Layer:
   Another 2D convolutional layer (Conv2D) with 32 filters of size 3x3 is added, again using the 'relu' activation function and 'he_uniform' kernel initializer.

4. Second Max Pooling Layer:
   Another max pooling layer (MaxPooling2D) with a pool size of 3x3 is added after the second Conv2D layer to further reduce the spatial dimensions of the output feature maps.

5. 3rd Convolutional Layer:
   A third 2D convolutional layer (Conv2D) with 32 filters of size 3x3 is added, using the 'relu' activation function and 'he_uniform' kernel initializer. a third 2D convolutional layer (Conv2D) has been incorporated into the system. This layer is comprised of 32 filters, each with a size of 3x3. The 'relu' activation function and 'he_uniform' kernel initializer have been applied to this layer to optimize its performance. By adding this layer, the system can potentially improve its ability to detect and analyze features within the input data.

6. Third Max Pooling Layer:
   Another max pooling layer (MaxPooling2D) with a pool size of 3x3 is added after the third Conv2D layer to further reduce the spatial dimensions of the output feature maps.

7. Flattening Layer:
   After passing through the third MaxPooling2D layer, the resulting output feature maps are flattened into a 1D array. This is accomplished using the Flatten layer, which transforms the 2D output of the convolutional layers into a 1D array suitable for input into the subsequent layers of the system. This step is crucial for processing the data in a way that can be interpreted and used by the following layers of the network.

8. Dense Layer:
   On top of the Flattening layer, a fully connected layer (Dense) has been added to the system. This layer contains 64 units and utilizes the 'relu' activation function to facilitate the nonlinear transformation of the input data. The addition of this layer allows the system to further analyze and process the feature maps extracted by the convolutional layers, which may enhance the system's ability to perform its intended function.

9. Dropout Layer:
   To address the potential issue of overfitting, a Dropout layer has been incorporated into the system. This layer randomly drops 50% of the inputs during each training epoch, which can help to prevent the network from becoming overly specialized to the training data and improve its generalization performance.

10. Output Layer:
    The output layer is a fully connected layer (Dense) with a single unit and 'sigmoid' activation function, which outputs a probability of a tumor being present in the input image.

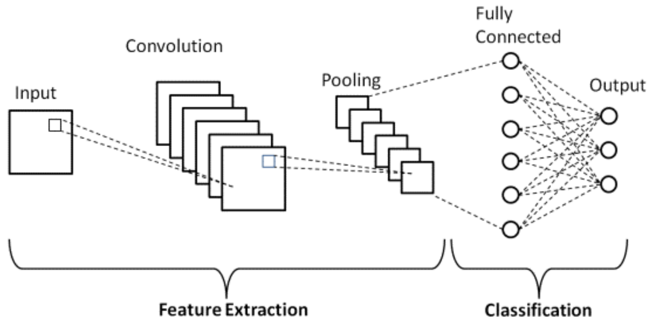


Fig: Architecture in Brain Tumor Detection

## V. IMPLEMENTATION

**Data Augmentation**: By producing altered reproductions of the original photos, the approach of "image data augmentation" allows one to increase the size of a training dataset. Deep learning models' capacity to generalise and perform effectively on new images can be enhanced by expanding the amount of data used to train them. The capacity of the model to recognise important elements can be improved further by using data augmentation techniques to produce several versions of the images[1][2][3]. The visual Data Generator class in the well-known deep learning framework Keras makes it simple to incorporate augmented visual data during model training.

number_of_augmented_images = number_of_images * number_of_transformations
where number_of_images is the number of images in the dataset and number_of_transformations is the number of transformations applied to each image.

**Image acquiring:** To ensure thorough coverage of the topic, wide-field-of-view photos must be acquired during the first stage of the image processing pipeline. The MATLAB 'uigetfile' and 'imread' functions can be used to get the input photographs from a repository. With the help of these features, users can choose and load image files from a directory or other storage location. The required input data can be acquired and prepared using these routines for later processing and analysis.

Each input x (image) has a shape of (300, 300, 3) and is fed into the neural network. And, it goes through the following layers:

1. A Zero Padding layer with a pool size of (3, 3).
2. A convolutional layer with 32 filters.
3. To speed up calculation, a batch normalisation layer normalises pixel values.
4. ReLU activation layer.
5. A Max Pooling layer with f=3 and s=3.
6. A layer called "flatten" that turns the three-dimensional matrix into a one-dimensional vector.
7. Given that this is a binary classification problem, a dense (output unit) fully connected layer with one neuron with sigmoid activation should be used.

**Data split**
The data were divided as follows:
80% of the information is for training.
ten percent of the data for verification.
10% of the data are being tested.
educating the model The split data are trained with a test size value of 0.3 in this method.
There are 3060 training examples.
There are 310 development examples.
310 test instances total.
Shape of the X-train: (1500, 300, 300, 3).
Shape of Y_train: (1500, 1)

**Validation**:
The loss and accuracy are plotted in a graphical representation for easier understanding, as shown:

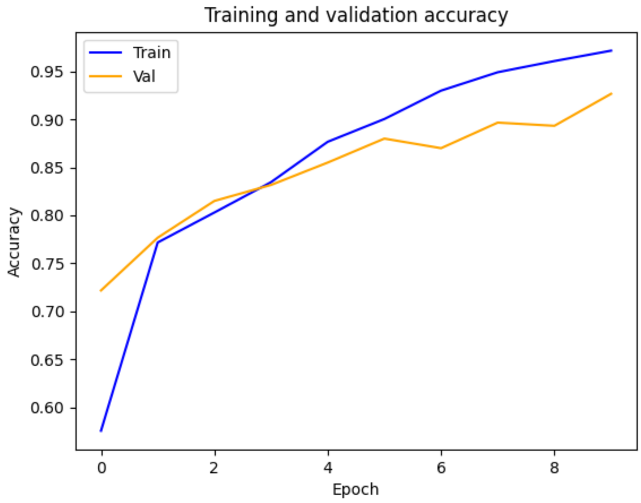


Fig: Accuracy rate

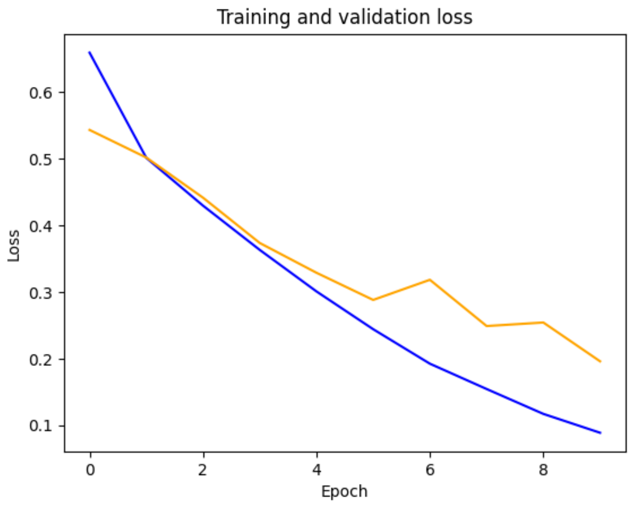


Fig: Loss rate

## VI. RESULTS


Fig: Positive Output


Fig: Negative Output

## VII. CONCLUSION AND FUTURE WORK

In conclusion, Convolutional Neural Networks (CNNs), in particular, have shown a lot of promise in recent years for application in deep learning methods for the diagnosis of brain tumors. The excellent accuracy rates attained by these models show their potential to help doctors identify and diagnose brain tumors early, which would improve patient outcomes.

The effectiveness and precision of the detection procedure have significantly increased thanks to CNNs' capacity to examine massive amounts of medical imaging data and spot tiny patterns and traits that could be indicative of a brain tumor. The likelihood of false negatives or false positives, which can have detrimental effects on patients, can be significantly decreased by the usage of CNNs.

Overall, the creation and application of deep learning methods in the area of diagnostic imaging and healthcare technology represent an interesting breakthrough. Future accuracy rates and patient outcomes are projected to increase as CNNs and other deep learning models continue to advance.

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